Paper 170-2010

An Analytical Approach to Determining Customer Value in the Property and Casualty Insurance Industry

Roosevelt Mosley, FCAS, MAAA, Pinnacle Actuarial Resources, Inc., Bloomington, IL

ABSTRACT

The traditional actuarial focus has been to price with an eye on profitability over the next six to eighteen months. However, most corporate goals contain a desire for long-term profitability. This can create a disconnect between the prices charged by insurers and the long-term goals of the company. This paper will explore the components of customer value and how actuaries and analysts can use this information to make more profitable short-term decisions.

We propose to use an actual case study to:

1. Discuss the components of customer value, including profitability, and the probability of attracting, converting and renewing a risk.
2. Discuss how competition affects the ability to write and retain risks.
3. Discuss how to quantify the elasticity of demand using the company's own renewal and conversion information supplemented by public information.
4. Highlight the differences between decisions made using traditional approaches and a long-term customer value approach.
5. Discuss the practical considerations of implementing these concepts.

INTRODUCTION

The concept of customer value has been the topic of significant interest within the insurance industry. Everyone, regardless of the industry, understands that there is a difference in the value of certain types of customers. This difference significantly impacts the current and future profitability of an insurer. However, because of some of the unique features of the insurance industry, this definition of value is not always consistently reflective of truly more or less valuable customers. In this paper, we discuss a method for applying a consistent, analytical approach to the definition of customer value for insurers. This value takes into account true profitability of an insurance company risk, as well as the future likelihood of realizing that value. Through the use of predictive analytics, we will discuss the development of estimates of each of the components of customer value, and how the determination of customer value can lead to more effective business decisions. We will also discuss some of the practical issues that arise when taking a more analytical view of customer value.

This paper builds upon concepts introduced in a paper by Sholom Feldblum entitled "Persistency and Profits." (Feldblum, 1990). This paper discusses the application of predictive analytic techniques to the concepts described in Feldblum's paper, and also provides examples of results from performing this type of analysis.

DEFINING CUSTOMER VALUE

Defining customer value seems like a very straightforward concept, but there are challenges within insurance which make the definition of customer value more challenging. First, when pricing insurance, insurers are charging a premium for a product before the actual costs of the product are known. Data is analyzed from prior years to determine a premium that is appropriate for the risk, but there is still a level of uncertainty present because potential future events are being insured. Secondly, property and casualty insurance companies are heavily regulated, and this regulation places limitations on what a company can charge an insured, and how this premium can change from year to year. Third, insurance companies have a lot of institutional knowledge rooted in the way insurance was priced and managed prior to the late 1990's. The risk characteristics used to rate insurance policies were limited, there was not a significant differentiation in the elements that were used in different insurance company rate calculations, and as a result the premium differentiation between companies for the same insured was not significant.

These, plus other influences and considerations, have led to several different ways of determining which customers are more valuable. One of the ways that customer value is defined by some insurers is by defining what they consider to be risks that pose a lower likelihood of having a claim. In auto insurance, for example, this has traditionally been thought of as risks that are middle aged, have multiple cars, buy multiple lines of insurance from the same company, have a good claims history, and have a good credit based insurance score. Other companies have defined valuable customers as those which fall within a particular niche area of the market. Because historically insurance products were thought of as commodities, one way to distinguish yourself as a company was to focus on particular segments of the market. There are many insurers that focus on particular groups, such as auto club members, teachers, farmers, etc. For these companies, they define their particular customer segment focus as more valuable. Another definition of customer value centers around segments of insurance business where it is felt that the rates are most adequate. If the company can charge a premium that it feels is adequate for the risk being undertaken, that increases the expected profitability and thus the value of the risk. This is often determined by measures such as historical loss ratios (ratio of losses incurred by the company to premiums charged), and these results are often reviewed by broad summarizations (age, years insured with the company, etc.). Other definitions of value focus on the success of attracting and retaining particular types of risks. If a company has been particularly successful at writing certain classes of business, this business may take on a higher value to the company.

While many of these definitions of customer value are important, none of them capture all of the elements of customer value. If an insured poses a lower likelihood of having a claim over the policy period, it does not automatically make them a more valuable risk. Many companies are competing for these lower claim frequency insureds, which leads to lower prices and reduced profitability. If an insurance company is good at writing a particular niche or segment of the market, it does not mean every risk within that niche has the same customer value to the company. Even within a tightly defined market segment there could be wide variations in customer value. Having profitable experience for a particular segment of the business does not necessarily point to a more valuable customer if the company is not able to consistently attract or retain these customers for a significant length of time. Success at writing a particular class of business is not by itself a measure of value if an insurance company is unable to charge rates that are adequate for that class of business.

There are broader issues with these and other definitions of customer value within insurance. First, the definitions can sometimes be subjective. The definitions may have been historical determinations of what was valuable to the company, or based on the experiences of certain managers and employees within the company. The problem with subjective definitions, especially when they are not rooted in data analysis, is that they may not be consistent over time or even based in fact. In addition, the definitions can be short term in their view. Looking at recent statistics on losses, new business conversion and retention can lead to decisions to fix short term issues, but may not lead to understanding the customers with the greatest long term value. The other issue that these different definitions of value can raise is that they may reinforce silos within an insurance company. For example, the marketing department might see a valuable customer as one who responds to marketing initiatives, but the actuarial department might see a valuable customer as one who the company can expect to make a target profit on. If these customer descriptions do not match, it can lead to inconsistent actions within a company. Without a consistent company view of customer value, sub-optimal decisions can be made by different departments.

To address the issues in defining a valuable customer, there needs to be a definition of this value that takes into account all of the elements important in determining value, and one that can be consistently applied across an insurance company organization. Broadly defined, this definition of value centers around two elements:

1. The expected profit for a particular risk, and
2. The likelihood of making that profit over the time period being analyzed.

For existing business, this value can be defined at a customer level by the following equation:

$$\text{EVEB} = \frac{P_1 \times (1 - C_1)}{(1 + r)} + \frac{R_1 \times P_2 \times (1 - C_2)}{(1 + r)^2} + \frac{R_2 \times P_3 \times (1 - C_3)}{(1 + r)^3}$$

where EVEB = Expected Value of Existing Business
P_i = profit at time i = Premium – E(Loss) – Expense
C_i = probability of cancellation during period i
R_i = Probability of renewal at the end of the period i
r = discount rate

This calculation just covers the next three policy periods, and assumes that profits are realized at the end of the year. Additional terms can be added to extend the calculation further, and adjustments can be made to better reflect the timing of the receipt of premiums and the payments of losses and expenses.

This measure of value can be extended to potential customers as well. Once a potential customer receives a premium quote from an insurance company, they have the option of either accepting or rejecting that quote. So the expected value of business that has been quoted (EVQB) is the EVEB adjusted for the probability that the customer accepts the quote. Prior to the business being quoted, there is often a targeted marketing list or potential customer list that can have a customer value associated with it. The expected value of targeted business (EVTB) is the EVQB adjusted for the probability that the marketing target responds to the marketing initiatives.

This definition of insurance customer value is based on measurable elements that can be estimated through the use of predictive analytics. This definition is also one that can be measured at the customer level, and then an aggregate book of business value can be built up from the individual customer values. In addition, this is a measurement that can be used to build more consistency across an organization, with each area understanding how their individual actions impact customer value measures. Lastly, through the use of predictive analytics, this definition is prospective, looking at customer value over the future expected life of the risk.

MEASURING THE ELEMENTS OF CUSTOMER VALUE: EXPECTED LOSS

Measuring the critical pieces of insurance customer value can be accomplished by the use of predictive analytics. For the prospective elements of customer value, based on historical experience and what we know about an insurance risk we can use predictive analytics to develop models that will calculate expected customer value. For this case study, this was accomplished using SAS® Enterprise Guide® and SAS® Enterprise Miner™.

The first element required to understand the expected customer value is the expected profit. The expected profit, as shown above, is simply:

$$P_i = \text{profit at time } i = \text{Premium}_i - E(\text{Loss}_i) - E(\text{Expense}_i)$$

PREMIUM

For most personal lines insurance companies, the auto and homeowners insurance premiums are a deterministic number. Insurance company rating plans have to be filed with state insurance departments in most jurisdictions. In all states, once a personal auto or homeowners premium rating plan has been established, a company can not deviate from this rating plan without first filing a new rate plan. While it is true that most companies review and adjust their premium rates at least yearly, they do so in response to changes in loss experience. As losses increase, premiums increase, and as losses decrease, premiums decrease. Therefore, while it is not reasonable to assume that premiums will not change in the future, it is reasonable to assume that they will over the long term retain a constant relationship to losses. There will be lag periods where this relationship is not maintained due to delays in analyzing loss experience and in making rate filings to change rates. However, as the speed of data reporting and analysis continues to increase, this lag will get shorter and shorter. So we will assume that premium calculations remain constant over some future period.

For commercial lines insurers, there is more flexibility to adjust premiums based on the specific risk being insured. This is because commercial lines insureds are more heterogeneous, and there is flexibility maintained by commercial lines insurers to adjust premiums to reflect specific insured differences. While the long term constant relationship between losses and premium will still hold, there will likely be longer periods where the short term relationship deviates significantly from the long term average. While beyond the scope of this paper, one area of additional research would be estimating these expected deviations and how they vary by type of risk.

EXPECTED LOSS

The first significant analytics exercise in determining insurance customer value is analyzing the expected loss of a insured. Many companies in the insurance industry have begun to use predictive analytics for the purpose of developing rating plans, but with some limitations. The first limitation has been regarding the analytic techniques used. Many rating plan analyses have used Generalized Linear Modeling (PROC GENMOD) to analyze the expected claim frequency (the likelihood of a risk having a claim), the expected claim severity (the expected cost of a claim), the expected pure premium (the overall expected loss per insured), or the expected loss ratio (ratio of incurred losses to premiums charged). Generalized Linear Models have been used for years in other countries such as the United Kingdom, and have gained acceptance across the United States within the insurance company and the regulatory communities.

The second limitation in many insurance company rating plan analyses is that the analysis is often based on a limited number of independent or explanatory variables. There are a number of reasons for these limitations, including objections from insurance regulators, reluctance by insurance companies due to the potential reaction from their customers, and the lack of an intuitive relationship between the independent variable under consideration and insurance losses.

To develop a measure of expected loss, an insurance company's first inclination might be to just use the results of the rating plan analysis to estimate expected losses. While the use of predictive analytics for the rating plan analysis makes the best use of the data available, the analysis of expected loss should be expanded to include more available independent variables as well as to apply additional techniques to get a more accurate picture.

There are many additional independent variables that an insurer can use to understand the true expected loss cost of an insured. These independent variables can come from a number of additional sources, both internal to an insurer and from external sources. These sources can include:

- Actuarial

  Traditionally identified rating characteristics include elements such as age, driving history, vehicle type, credit score, and vehicle use. However, there are times when, due to regulatory or operational considerations, certain characteristics cannot be used. For example, there are certain states where the gender or marital status of person cannot be used to rate insurance. In these situations, even though the law prohibits a company from distinguishing premiums based on a particular characteristic, it does not mean that this characteristic is not important in determining the true expected risk that an insurance company is taking on. There could also be cases when a new potential rating characteristic cannot be used immediately by an insurance company due to operational considerations (systems, workflow, etc.). Even in cases where a characteristic cannot be used to establish premiums for an operational reason, it should not prohibit it from being used in understanding the expected cost.

- Underwriting

  Traditional underwriting focused on selecting insureds based on characteristics that may not have been traditionally rated on, but were still important in understanding the risk being undertaken. In homeowners insurance, for example, part of the underwriting process includes inspecting the home and assessing the condition of the home, how well the home as been maintained, and potentially recommending corrective action to the homeowner to make the risk acceptable to the insurer. While some of the information determined during the underwriting process can be qualitative, there are opportunities through the use of data analysis and text mining techniques to turn this information into a valuable part of understanding the expected costs of an insured.

- Agency

  Many companies use captive or independent agency forces to sell and service their insurance policies. These agents bring a human element to the insurance process that has a real impact on the expected loss potential of an insured and a book of business. Typically, the agents have a relationship with the insured and represent the first line of underwriting for the insurer. And like any other influence on the insurance process, different agents impact the process differently. By making the agent a part of the analytic process, you can assess the amount of value that an agent adds or detracts from the book of business that they produce. While it would be impossible to set up a rating plan that differentiates premiums based on the agent an insured goes to, it is easy to include the agent as an influence on expected costs.

- Billing

  There are a number of elements based on insurance policy billing that can be used to understand the expected cost of an insured. These elements include the selection of the billing plan (annual payment vs. monthly payment), type of payment (credit card, electronic funds transfer, etc.), and payment history with a company. The payment history can include the number of late payments, the number of days late a payment is, and the number of non-sufficient funds charges. This can also include elements of billing such as the number of cancellation notices and actual historical cancellations. While some of these elements are already being used by insurers in rating plans, there are others that can be used to refine the expected cost estimates.

- External Data

  There are many external data elements that are available to insurers that can be used to enhance the expected loss calculation. These external elements include items such as household and individual level allowable demographic information. This information has been developed more for marketing purposes, however it can be used to better understand risk. This includes information such as shopping habits, stage of life, and household characteristics.

- Account Information

  When assessing risk levels, if an insurer writes multiple lines of insurance within a household, information from those additional lines can be used to understand the risk. For example, when writing an auto insurance policy, the characteristics and loss experience of the homeowners line of business can be used to better understand the expected auto losses.

In addition to using more explanatory variables to assess insurance risk, when internally attempting to understand expected losses, additional predictive analytics techniques can be used to better predict future loss costs. As described above, Generalized Linear Models have become generally accepted for the development of insurance pricing plans. However, there are situations where the prediction of losses could be enhanced by the use of additional techniques.

To illustrate the difference in the results of the expected loss calculation when using more independent variables and additional analytic techniques, we performed an analysis of auto insurance losses from the comprehensive coverage. Specifically, we analyzed expected claim frequency and expected claim severity based on three years of loss history. This analysis was performed in SAS® Enterprise Miner™ using two sets of independent variables.

1. Using only independent variables that were used in the calculation of premium, and
2. Using all available explanatory variables

Using additional explanatory variables can show significant differences in expected losses. The example below shows the difference in auto comprehensive expected claim frequency based on the number of claims filed in the last five years for another line of insurance. For insureds that have filed a claim in the last five years for the other line of insurance, the likelihood of having an auto claim increases by about 19%.

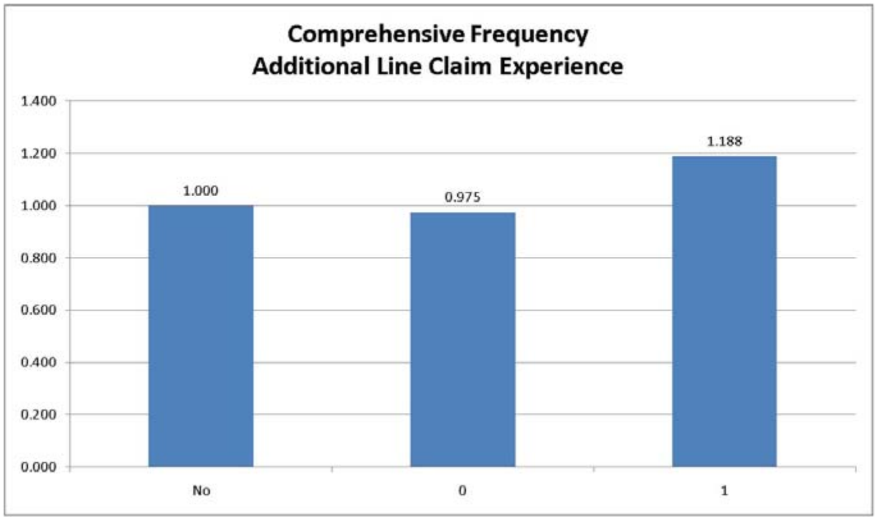

Figure 1: Comprehensive Frequency Additional Line Claim Experience

The effect of additional claim variables can also be seen also be seen on the expected cost of a claim. Below is the impact of the age of home on expected auto comprehensive claim severity, showing that the expected cost of an auto comprehensive claim increases as the age of home increases.

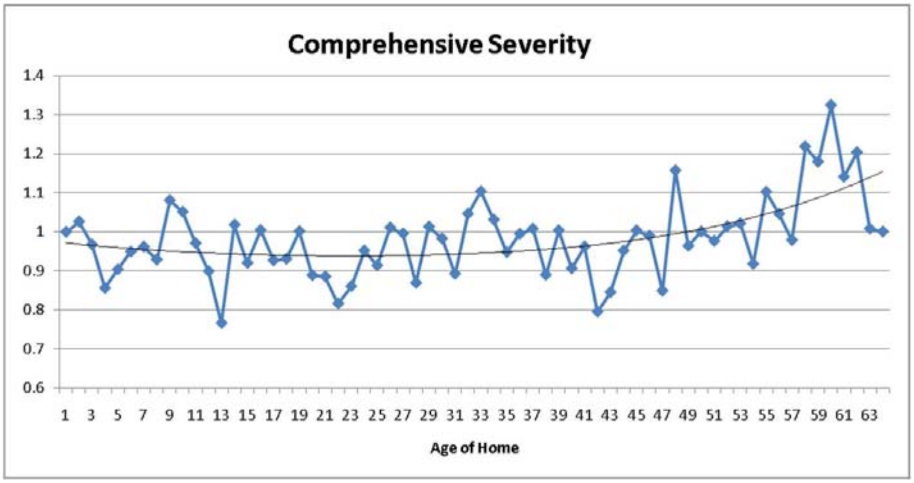

Figure 2: Expected Comprehensive Severity by Age of Home

In addition to testing additional independent variables, we also have applied additional modeling techniques using SAS® Enterprise Miner™ to develop additional estimates of expected claim frequency and expected claim severity. The techniques we applied were:

1. Generalized Linear Models
2. Decision Trees
3. Neural Networks.

The following is the Score Rankings Matrix based on the application of PROC GENMOD with a Gamma error structure and a log link function to a claim severity analysis.

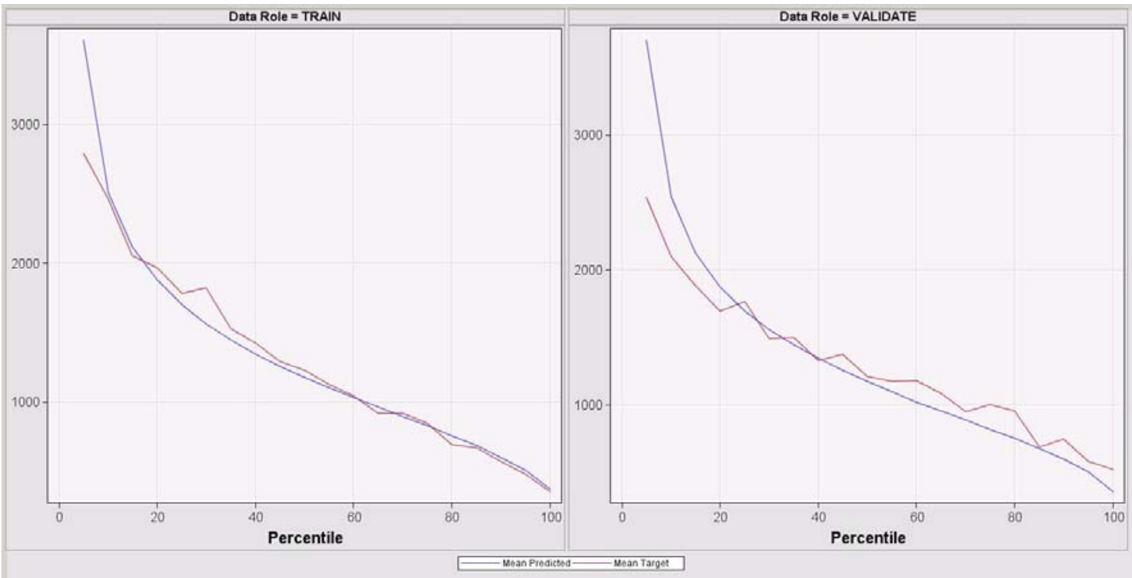

Figure 3: Score Rankings Matrix from Comprehensive Severity Analysis

As can be seen in the figure above, as the mean target claim severity increases, the mean predicted claim severity increases at a faster rate. This occurs partially because PROC GENMOD represents a linear technique, and as the risk level increases, PROC GENMOD does not adequately reflect the moderation in risk that occurs at the highest risk levels. To address this issue, we developed a Decision Tree to better predict claim severity at the higher mean target levels. We then developed an Ensemble model incorporating the Generalized Linear Model and the Decision Tree. After running a model comparison on the Generalized Linear Model, Decision Tree and Ensemble Model, the Ensemble Model improved on the prediction based solely on the Generalized Linear Model. As seen from the Score Rankings Overlay below, the Ensemble Model has a moderated prediction at the highest predicted severity levels.

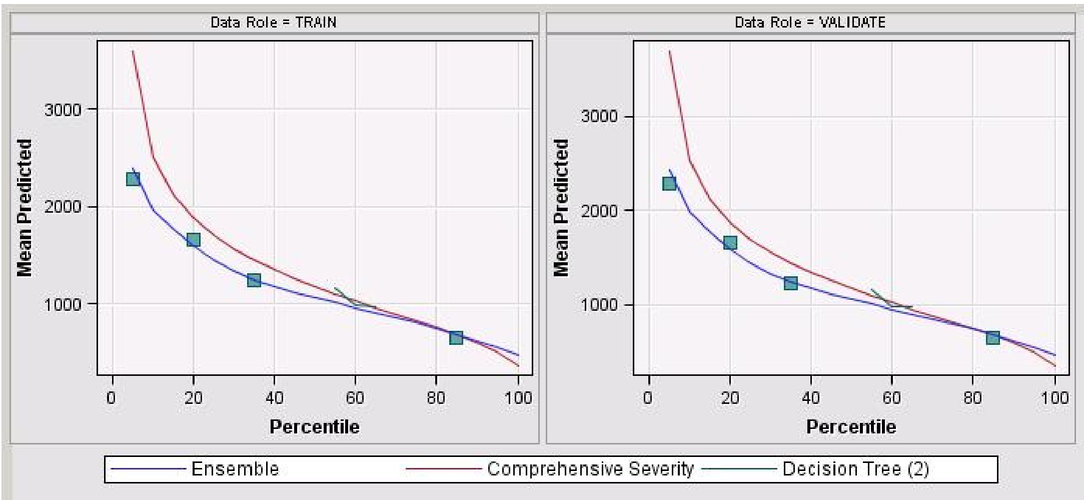

Figure 4: Score Rankings Overlay for Model Comparisons

The difference in the predicted loss costs can be significant when adding additional explanatory variables. We developed Generalized Linear Models using just rating characteristics, and also using all available significant characteristics. Based on this analysis, we calculated the predicted claim frequency for each risk in the database for each analysis. We then calculated the percentage difference in the predicted frequency for the rating plan analysis versus the predicted claim frequency from the analysis including all the variables. As can be seen in Figure 5, the difference in predicted claim frequency can be significant. In this example, about 15% of the risks see an increase in predicted claim frequency of over 25%, and about 19% of the risks see a decrease in predicted claim frequency of over 25%. Based on this analysis, the use of the rating plan analysis to estimate expected losses could lead to a significant understatement or overstatement of expected customer value.

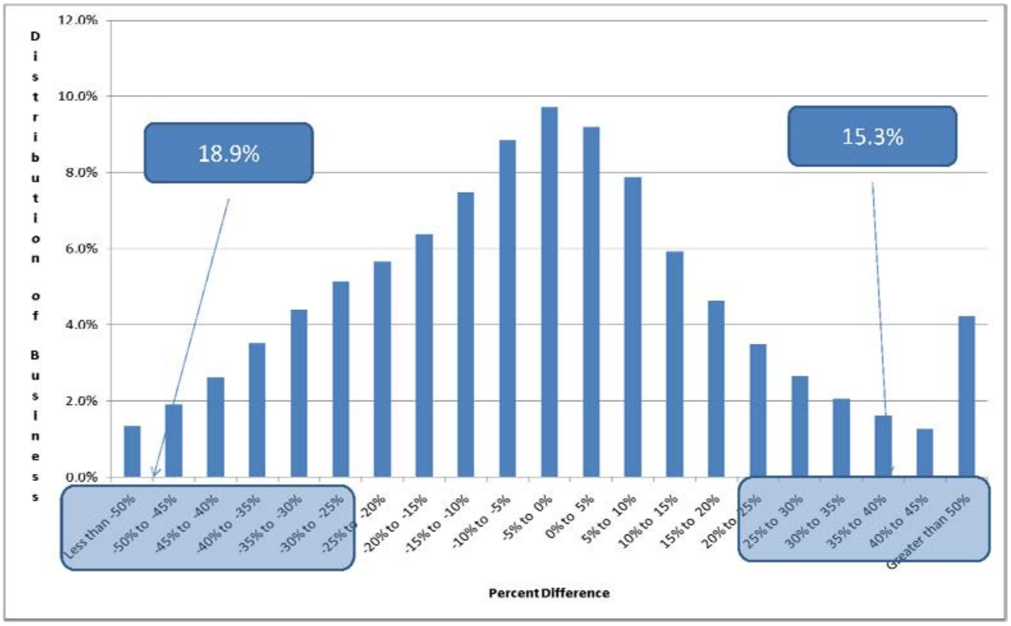

Figure 5: Difference Between Full Model and Rating Plan Model

EXPENSES

For this case study we have not included a separate analysis of expenses. For insurers, as with many other industries, many expenses are not directly assigned to individual customers, and therefore are often allocated in aggregate. Since the purpose of this analysis is to develop a customer level expected value measure, the simplest approach to incorporate expenses would be to subtract either a fixed percentage of premium from each insured's expected profit and/or subtract a fixed dollar amount from each insured's expected profit. While this approach would change the overall expected profitability number for each risk, it would not change the relative profitability levels between risks. In this case, the inclusion of expenses would be deterministic.

There are, however, certain expenses that an insurer incurs that can be allocated more directly to specific classes of customers, and these allocations could help to refine the calculation of the individual expected profit. One class of these expenses is general claim expenses. When an insurer settles a claim, expenses that an insurer incurs specific to that claim are usually assigned to that individual claim. An example of this is the cost of retaining an attorney in cases where lawsuits are involved. However, there are a number of general claim expenses that cannot be attributed to any specific claim. These expenses include claim adjuster salaries and the cost of maintaining claim service offices. While these types of expenses cannot be attributed to specific insureds, they can potentially be better allocated to classes of insureds. For example, if a risk is more likely than another to have a claim, then a larger portion of the general claims expenses should be allocated to the risk that is more likely to have need of the claim services.

Another example of expenses that could potentially be better allocated is marketing expenses. Marketing expenses are becoming a larger portion of insurance company expenses, and these expenses are incurred largely for the purpose of attracting new customers to the company. Therefore, when combining the results of an expected customer value analysis, adjusting the expected profit to account for the increased cost of obtaining new business could provide for a more accurate picture of expected profit.

EXPECTED PROFIT

Once the expected loss has been calculated, the next step is to calculate the expected profit. This is done by simply subtracting the expected loss from the premium that is charged (ignoring expenses). In theory, insurance premiums are established with the goal of making a target profit regardless of the class of risk being insured. In practice, because of a number of influences on premiums, even though the overall average target profit might be appropriate for a book of business, when measured at an individual risk level the expected profit varies significantly. The following chart shows the distribution of expected profit based on the analysis described above.

Figure 6: Distribution of Expected Profit by Individual Insured

There are several things that are apparent from the chart shown in Figure 6. First, there is a significant spread in the expected profit by risk. In this particular example, there were individual risks that had calculated expected losses more than 10 times greater than the premium being charged. As can also be seen from the chart above, there were almost 3.5% of the insureds that had an expected profit of over 90%. In other words, the premium was more than 10 times greater than the expected loss. In addition, there a significant left tail to this distribution. Because this particular example does not contemplate expenses, the break-even point for the insurer in this example is about 30%. This means that over 25% of the risks insured have an expected profit of 30% lower than the break-even point (less than 0% on the graph above). Lastly, the mode of this distribution is 60 – 70%, which is roughly 30% higher than the break even point. This reinforces the point that there are a significant number of customers whose higher than average expected profits are making up for the losses of a smaller number of customers that have significantly higher than average expected losses.

MEASURING THE ELEMENTS OF CUSTOMER VALUE: CUSTOMER RESPONSE

The second piece to measuring expected customer value is understanding customer response. During many stages of the insurance process, a current or potential customer has the opportunity to accept or reject the company as an insurer. It is this likelihood of customer response that adjusts the expected profit by the likelihood of actually making that profit. This paper focuses on three specific types of customer response analyses, as shown below.

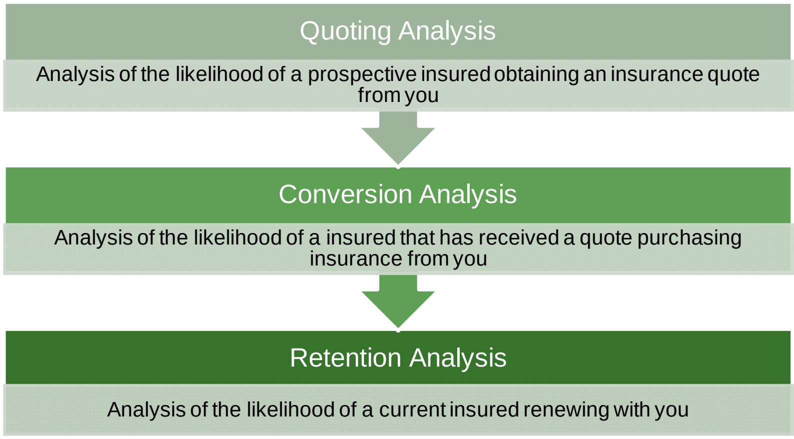

Figure 7: Customer Response Analyses

QUOTING ANALYSIS

Of the three types of customer response analyses shown above, the quoting analysis can be the most difficult to perform. This is generally because there is the least amount of data available on target populations, and historically the success of marketing efforts at the individual risk level has not be tracked very well. The purpose of this analysis is to understand the likelihood of prospective risks within a target population contacting an insurance company to obtain a quote for insurance. The results of this analysis can result in smarter use of marketing dollars, since it focuses on indentifying risks with a higher likelihood of responding to a company.

The first step in this analysis is understanding the historical target population. This target population can be at different levels of granularity. This could be at the individual risk level, as generated by sources such as marketing lists or a list of customers from an affiliate, such as a bank or travel club. This could also be defined by larger classes of insureds, such as potential insureds within a target age range or potential insureds that live in a particular area. Next, information needs to be gathered about the target population. This can come from internal sources to the extent this information has been tracked and retained historically, and it can also come from external sources, such as the marketing databases described above and initial credit scoring screening.

An example of this type of analysis is shown below. The analysis was based on a population of visitors to insurance company websites, and the likelihood of those web site visitors to obtain a quote for insurance. A number of potential insured characteristics were considered, and each risk characteristic was evaluated for the significance of its impact on the likelihood of obtaining a quote. Three model types were used to estimate this probability: neural network, logistic regression, and decision tree. The average predicted likelihood of a website visitor obtaining a quote based on how they were referred to the company website is shown in Figure 8.

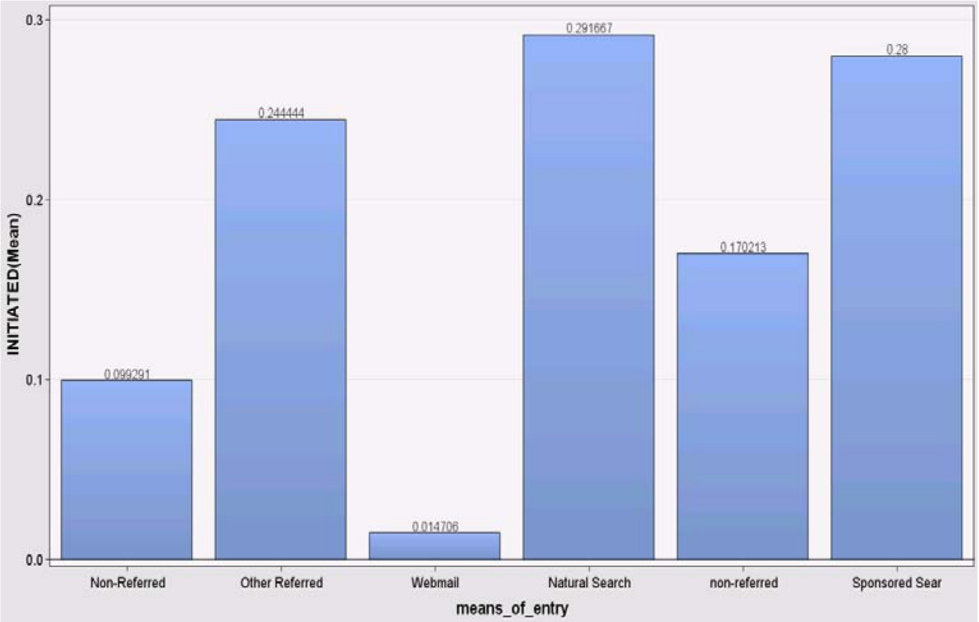

Figure 8: Likelihood of Obtaining a Quote Based on Means of Entry

As can be seen from the chart above, the likelihood of obtaining a quote increases for potential insureds that come to the company website as a result of a natural or sponsored search as opposed to other types of references.

The complete analysis of the likelihood of a risk to obtain a quote from an insurer generates a distribution of likelihoods that is very heavily weighted at very low probabilities, similar to what is shown below in Figure 9.

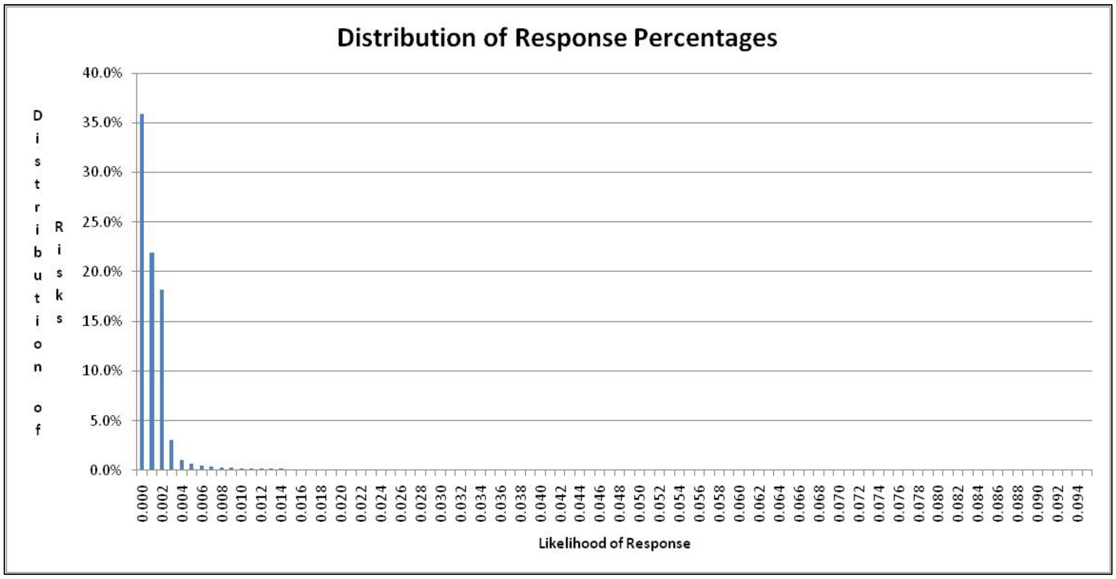

Figure 9: Distribution of the Likelihood to Obtain a Quote

In this particular example, although the distribution of risks decreases rapidly as the likelihood of response increases, there is still an estimated 10% of the population that is more than 20% likely to respond to a marketing initiative. This type of analysis can help companies better identify and target the risks most likely to respond.

Conversion and Retention Analyses

Although conversion and retention analyses are performed on separate populations, the structure of the analyses and the data elements used to perform the analyses are similar. A conversion analysis is an analysis of the likelihood of an insured to purchase a policy once they have received a quote from an insurer. A retention analysis is the analysis of the likelihood of a current insured renewing with you. There are a number of elements that can be used to better understand the likelihood of conversion and retention:

1. Traditional rating factors: Rating characteristics that are used to develop the premium for an insured can also be used to determine the likelihood of conversion or retention. Characteristics that have historically been shown to have value include age, insurance score, and accident and violation history.

2. Account characteristics: Elements related to the entire account relationship have also proven to be significant in predicting the likelihood of conversion and retention. These elements have included the number of policies written, the number of years insured (with current or previous carrier), and the change in premium.

3. Market conditions: This includes factors such as the competitive position of a company, whether the insurance market is currently hard or soft, and brand value of a company and its competitors.

A conversion analysis is used to better identify the risks that the company has been good at attracting, and can also identify where a company has problems competitively. A retention analysis helps to identify risks that are more likely to leave a company, and could also potentially point to either competitive issues or customers that are more sensitive to negative experiences with a company. In either case, insureds that are less likely to convert or renew can be proactively addressed to attempt to improve the conversion and retention rate, and risks that are more likely to convert or renew can be targeted and protected.

There are several data issues that can arise with retention and conversion analyses. First, with conversion analyses, new business premium quote histories are not always captured and retained, so it may be difficult initially to obtain a history of quotes and to determine which of those quotes were ultimately written as insurance policies. Also, with new customers, it is usually difficult to get an accurate premium from their previous insurer, so you may not be able to incorporate a new business price difference. For retention analyses, it is easier to build a historical database because the presence of a policy can usually be tracked from period to period. One potential issue can be the calculation of the renewal premium change if a policy does not renew. Insurers are not consistent in whether or not a transaction record is retained if a renewal policy offer is issued but not accepted. If a record is not retained, then there will not be a renewal premium change on any risks that do not renew. This becomes an issue as we discuss in the next section the influence of price change on customer value.

The likelihood of a risk to convert often is influenced by an insurer’s pricing structure and their marketing targets. In the example below, an insurance company was attempting to write more insureds with college degrees, and had set up a rating plan to provide significant discounts to insureds with college degrees. As can be seen from the chart below, the likelihood of insuring risks with higher levels of education was significantly higher.

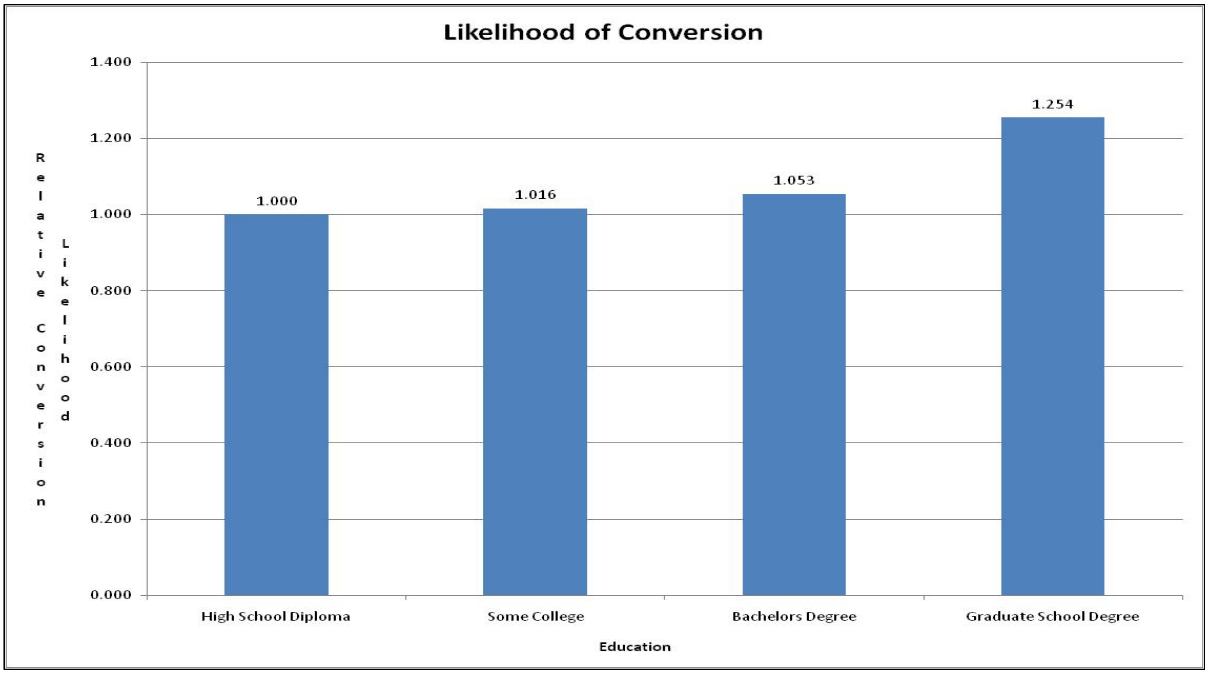

Figure 10: Likelihood of Conversion by Education Level

Using a logistic regression analysis, the likelihood of writing a risk increased by just over 5% based on a bachelor's degree, and by over 25% for masters degrees and higher. This was a case where the rating plan and marketing plan were working to accomplish the desired goal.

Companies have attempted to increase customer loyalty by becoming easier to do business with. One way companies have tried to accomplish this is by making it easier for customers to pay their premiums. This includes payment options such as Electronic Funds Transfer (EFT) and allowing credit card payments. An example of this is shown below.

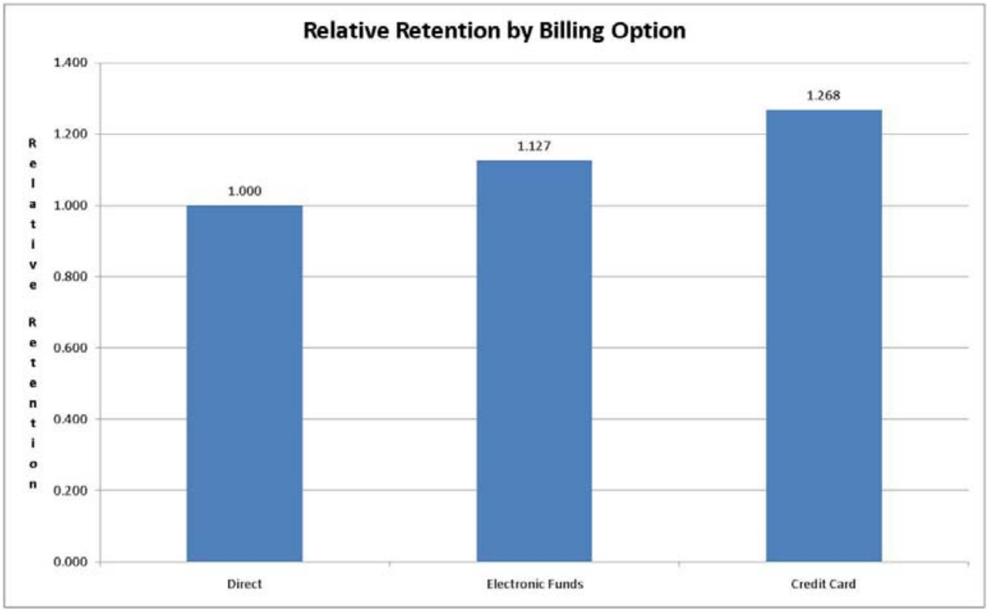

Figure 11: Predicted Retention by Billing Option

Based on a logistic regression model, the likelihood of a risk being retained by a company increases by about 13% when an insured pays by EFT, and by about 27% when the insured pays by credit card. This is an appreciable difference in retention that can be used to enhance long term customer value.

The ultimate result of these analyses is to develop a predicted conversion and/or retention based on the characteristics of a risk. These predictions can then be used to complete the calculation of expected customer value. To begin to pull the pieces together, in the chart below is shown the distribution of relative profitability (expected profitability by risk / overall expected profitability) by risk and the expected retention by risk group.

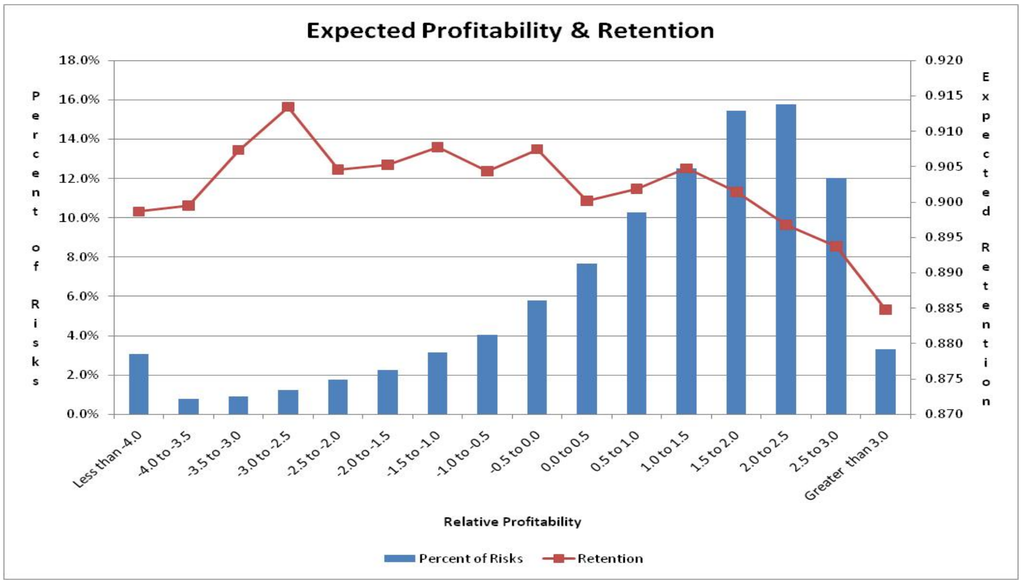

Figure 12: Expected Profitability and Retention

In this example, the expected retention for the most profitable groups of risks is about 1 - 2 points lower than the retention of the least profitable groups. If this trend were to continue, it would significantly impact the long term value of this book of business.

SIGNIFICANT INFLUENCES ON CUSTOMER VALUE

There are several elements that have a significant impact on the expected customer value of an insurance company risk, however are not as easy to measure. These elements are important because they have a significant impact on a company's ability to attract, write and retain insurance business. The two influences discussed here are the impact of competition and price changes on customer value.

IMPACT OF COMPETITION

Historically, rating plans of insurance companies were relatively simplistic, and because rates have to be filed with insurance departments, it was straightforward to calculate a competitor's premium for a particular risk. However, over the past decade, it has become much more difficult to calculate competitor premiums. There are a couple of reasons for this. The first reason is that insurers have become more competitive. A result of this competitiveness is that insurers have attempted to either hide portions of their rating plan from their competitors or make the rating plan very complicated and thus more difficult for competitors to decipher. Insurers have made use of approaches such as rating tiers and underwriting scorecards which have been considered by most insurance departments as underwriting guidelines, and therefore are not available to the public or competitors. In addition, insurers are using new rating characteristics such as credit score which are not easily translated from insurer to insurer, and therefore it is difficult to understand how a competitor is using it. Different companies may use different credit score algorithms, and each insurer uses different credit score rating bands which many times are not open to competitors. It is for these and other reasons that understanding the influence of competition is more difficult today than it has even been.

The competitive position of a company influences that company's ability to attract, write, and retain insureds. In addition, it ultimately impacts the prices that a company charges as companies make changes to their premiums based on the competition. Competitive position depends on more than just price, but also on other factors such as brand value and marketing activity. Ultimately, because of the influence of competition on customer responses, the effect of competition should be considered as a part of a customer response analysis.

There are several ways that the impact of competition can be considered in a customer response analysis. Regardless of the approach taken, because the effect of competition on customer response varies by customer segment and over time, incorporating competitive influence should be done at a segmented level and also should vary based on the time period covered in the data history. These approaches include:

1. Batch Competitive Quotes

   There are multiple sources from which an insurer can receive batch competitive quotes based on a selection of risks. These quote sources have the advantage that they come with the rates of specific competitors already included, and by specifying risk characteristics the competitor's quotes can be generated. They also are relatively easy to use for generating competitive quotes for a large set of individual risks. The concerns with competitive quote systems are that they suffer from some of the same limitations described above. Because of the increased complexity and secrecy with rating systems today, it can sometimes be difficult to match a competitor's rates exactly. Also, when using less transparent variables like credit scores and underwriting tiers, companies will need to make assumptions about where a particular risk fits in another company's rating system, and this can lead to further inaccuracies.

The competitive quotes can be generated on an insurers entire book of business, or they can be generated a market basket of risks that is diverse enough that the competitive quotes can be mapped back to individual policyholders. The competitive quotes should also include a representative sample of competitor companies. In the case that quotes are generated on the entire book of business, there are several options for how this information can be incorporated into a customer response analysis. The most direct approach would be to simply load each competitors rates back into the analysis dataset and use the competitors' rates as an independent variable. An approach to simplify this is to develop a ratio of the competitor's premium to the company premium, or a dollar difference between the company and competitor's premiums. This could be simplified even further by taking the difference between the company premium and the average or median of the competitors' premiums.

In developing competitor batch quotes, the competitors' rates should be calculated based on the historical effective dates of the risks. This is due to the fact that competitors' rates and competitiveness change over time. In addition, because the competitive position can vary by territory and by risk type, the analysis should include interactions between the competitive position and the other risk characteristics. This is an inherent part of techniques such as Neural Networks and Decision Trees, but for linear techniques such as Logistic Regression these interactions need to be specifically included.

2. <u>Segmented Market Share</u>

Another approach to understanding the impact of a company's competitive position is to review market share at a segmented level to determine how that market share relates to a company's ability to attract and retain insureds. Traditionally, insurers have measured their market share based on premium volumes at a statewide level. While this is helpful, it does not provide a complete picture. A market share based on premium would not be exactly equivalent to a market share based on the number of vehicles or the number of homes insured. Also, this does not allow a company to understand how successful or unsuccessful they have been at penetrating specific market segments within a state.

There are sources of information that a company can access which provide a better understanding of their vehicle or homeowner penetration at a more detailed level. This more detailed level for auto could include geography, make/model, model year, age, and marital status. For homeowners, this could includes geography, amount of insurance, construction type, etc. While this detailed market penetration will not get down to an individual risk level, it would introduce more refined estimates over some of the major rating characteristics in an insurance company book. These segmented market share totals can then be appended to a customer response analysis data base, and used as a proxy for competitive position to determine the ultimate influence on retention and conversion. This approach has the added benefit that it attempts to take into account some of the non-price related elements of competition.

An example of this segmented market share analysis is shown below. The chart below shows that the company had historically done a better job of penetrating the 45 – 74 year old driver market than the younger and older markets. This is one of the elements that could be used to develop a segmented market share measure that could be attached to a customer response analysis. The influence of this segmented market share on ultimate customer response can then be analyzed.

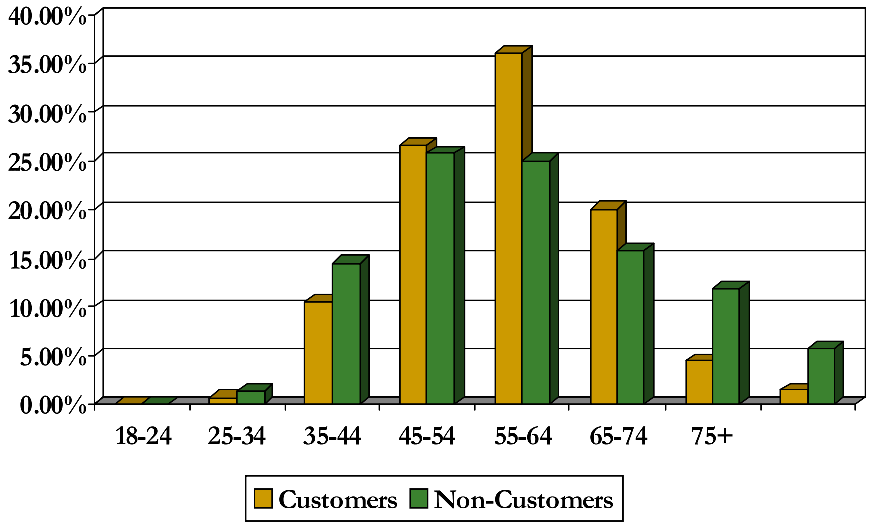

Figure 13: Market Penetration by Age

3. Rely on Customer Response Analyses

   Another approach to addressing the issue of competitive analysis is to not do anything specific to address the issue of competitive position, but to allow the results of the customer response analyses to alert you to potential competitive issues. For example, if certain groups of customers have a lower than average response rate as determined as the result of a quoting analysis, it can be concluded that part of the issue with the low response rate could be a competitive issue. Perhaps the company does not have the brand value in a potential customer's mind to entice them to respond. If a company has a lower than average conversion rate for particular segments of business that it is quoting or a lower than average retention rate for renewing customers, this could potentially point to a competitive issue with rates.

   This approach also takes into consideration competitive concerns other than price, and it alerts companies to where they are having potential competitive issues. This does not tell companies what the issues are, however, and will require the company to perform some investigation to uncover the source of these issues.

IMPACT OF PRICE CHANGES

When a company adjusts premiums, this will have an impact on expected customer value. It impacts customer profit as premiums change, but it will also have an impact on expected customer conversion and retention rates. In theory, as prices increase, expected profit will rise but expected conversion and retention will decrease. Conversely, as prices decrease, expected profit will decrease but expected conversion and retention will increase. It is the rate of change of the expected retention and conversion that will ultimately determine the impact of price changes on expected customer value.

Measuring the impact of price changes on expected customer retention and conversion is problematic for property and casualty insurers. The first issue is that insurance companies only change rates once or twice a year, and since many policies renew only once a year, there are not many opportunities for prices to change. Therefore, there is not a complete history of prices changing by incremental amounts and how customers react to those incremental price changes. The second issue is that since many risk characteristics change from year to year, prices change as a result, and these changes in price may or may not be changes that were anticipated by the insured. Therefore, it becomes a challenge to understand how a company's changes in rates compares to the customer's expectation. For example, if an insured has an accident, they generally expect their premiums to go up in the future. The key in this situation is not that the premiums go up, but how much the premiums go up relative to the customer's expectation. The third issue is that for many new business risks, companies do not have the accurate previous insurer's premium.

While these challenges are significant, they are not insurmountable. The starting point is for the company to analyze the price change history and its impact on retention and conversion, and then to use this to develop an estimate of customer price sensitivity. To address the issue of customer expectation, one approach is to measure the change in premiums assuming that all risk characteristics were to remain constant. This would require the new business or renewal premium for the customer response analysis to be calculated as if the previous policy characteristics did not change. A potential solution for the problem of not having old company premiums for new business is for insurers to use a competitive quote tool like those described above to get an estimate of the relationship of the new business premium to the old company premium.

These calculated price changes would be added as an element to the customer response analysis. As with the competitive analysis, the analysis of the impact of price changes on customer response should be done including interactions with the other characteristics used in the customer response analysis. The impact of price changes differs by customer segment, and the interactions help measure these differences.

An example of this is shown below in the results of a logistic analysis of customer response which included price change as a variable. Because of the data challenges described above, we do not have a complete picture of how customers react to price changes, but we can see general trends based on the data that we do have.

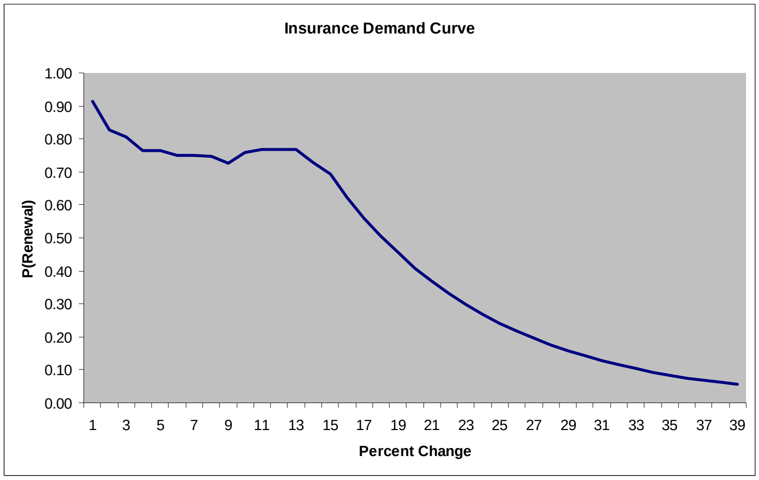

Figure 14: Impact of Price Change on the Probability of Renewal

As shown in figure 14, as price change increases, the probability of renewal decreases (level 13 represents no change in premium). In addition to this, partial interactions were included to see how the probability of renewal based on price changes should be adjusted for particular business segments. An example of this is shown below in Figure 15.

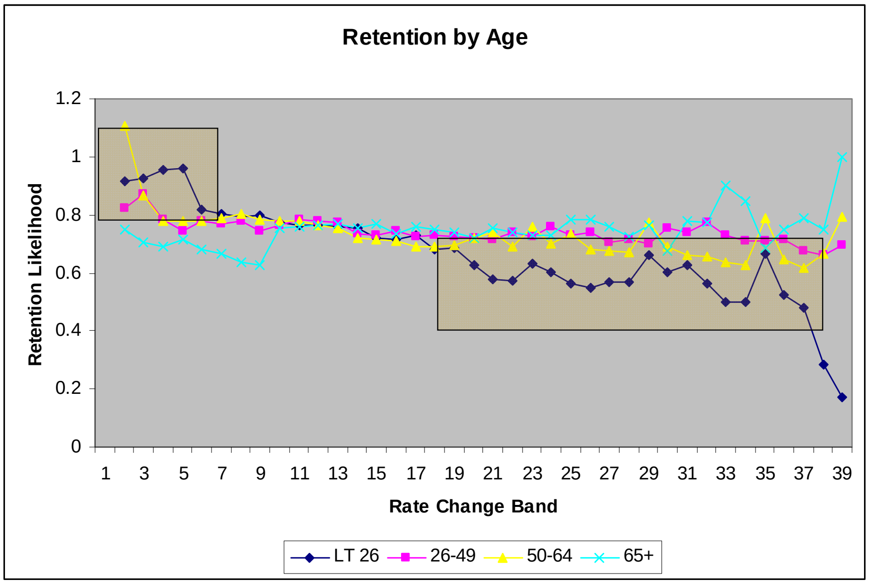

Figure 15: Likelihood of Retention by Age

As can be seen above, the likelihood of retention for risks younger than 26 is significantly higher for larger rate decreases and significantly lower for larger rate increases. This suggests that younger insureds are more price sensitive than older risks.

RESULTS OF A MORE EFFECTIVE MEASURE OF CUSTOMER VALUE

Recall the customer value formula discussed above.

$$EVEB = \frac{P_1 \times (1 - C_1)}{(1 + r)} + \frac{R_1 \times P_2 \times (1 - C_2)}{(1 + r)^2} + \frac{R_2 \times P_3 \times (1 - C_3)}{(1 + r)^3}$$

We have discussed using predictive analytics to estimate the elements needed to perform this calculation. The missing piece is the uncertainty inherent in projecting forward multiple years. We discussed earlier projecting the relationship of premium and losses into future periods. However there are also potential changes in risk characteristics that can be significant, and will significantly impact a customer’s expected value in the future. There are straightforward changes in risk characteristics such as changes in age and years insured that are easy to incorporate. There are also other changes that generally have to do with significant life changes that will impact premiums and expected loss. This could include getting married, having children, buying a new home or car, or moving.

One way to address these issues is to develop a series of “life change” models. Based on historical information in the database, models can be developed that estimate the likelihood of a significant change in risk status, such as the likelihood that a single person gets married. Based on these probabilities, additional elements can be taken into account reflecting the likelihood of a significant event occurring in the life of an insured.

When all of the elements of customer value are combined, the resulting estimated customer value of an existing book of business as compared to current customer value definitions can be surprising. The chart below shows the impact of including the first two terms of the calculation based on our case study, which covers the next two years.

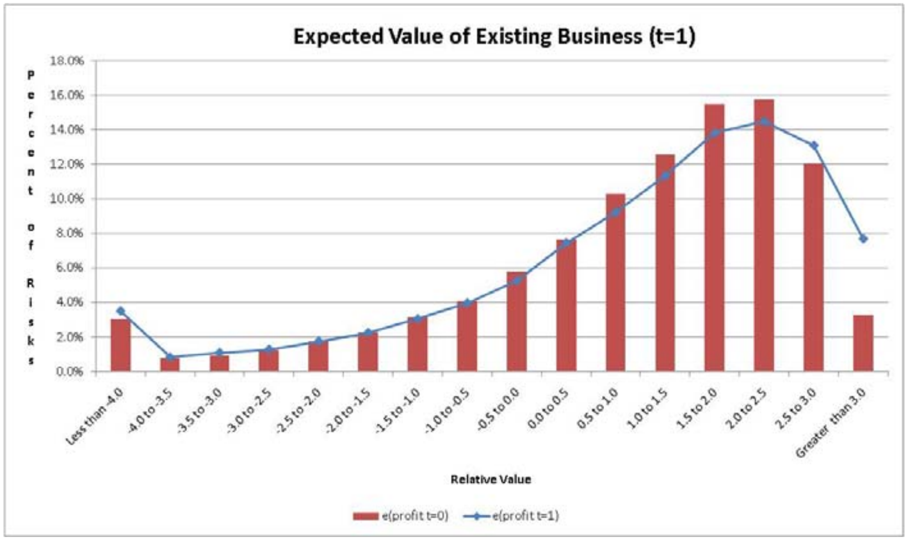

Figure 16: Expected Value Over the Next Two Years

As can be seen from this chart, the tails of the expected value over the next two years begin to shift outward. This is due to the fact that for many of the risks, the direction of the profitability does not change from year to year, so the likelihood of renewal makes the tails of the distribution more extreme. This distinction becomes more apparent as estimated value over the next four years is calculated.

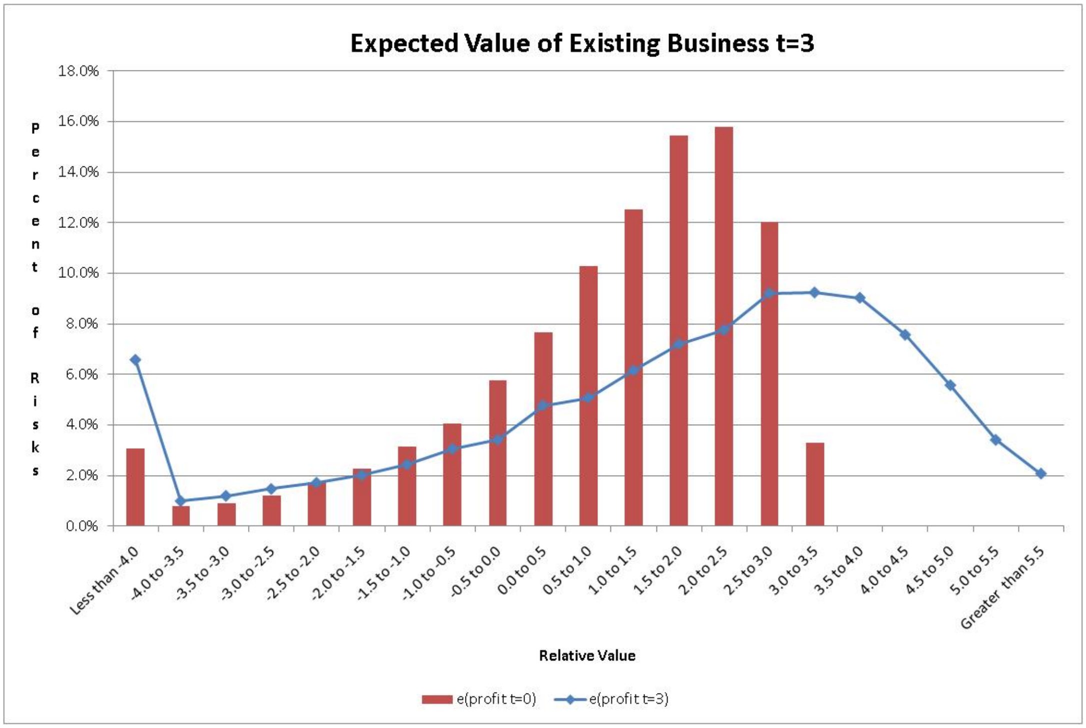

Figure 17: Expected Value Over the Next Four Years

Once this calculation has been performed, then a score can be developed to assist the company in understanding the characteristics of risks with higher and lower than average expected long-term customer value. This is accomplished by applying a linear regression model to the predicted customer values, and then reviewing the resulting scores to understand which levels of which elements indicate higher or lower customer values. An example of this is shown below, where the expected value increases as the age of the youngest driver in the household increases. The results of the scoring model can be used to build a profile of risks with higher expected value.

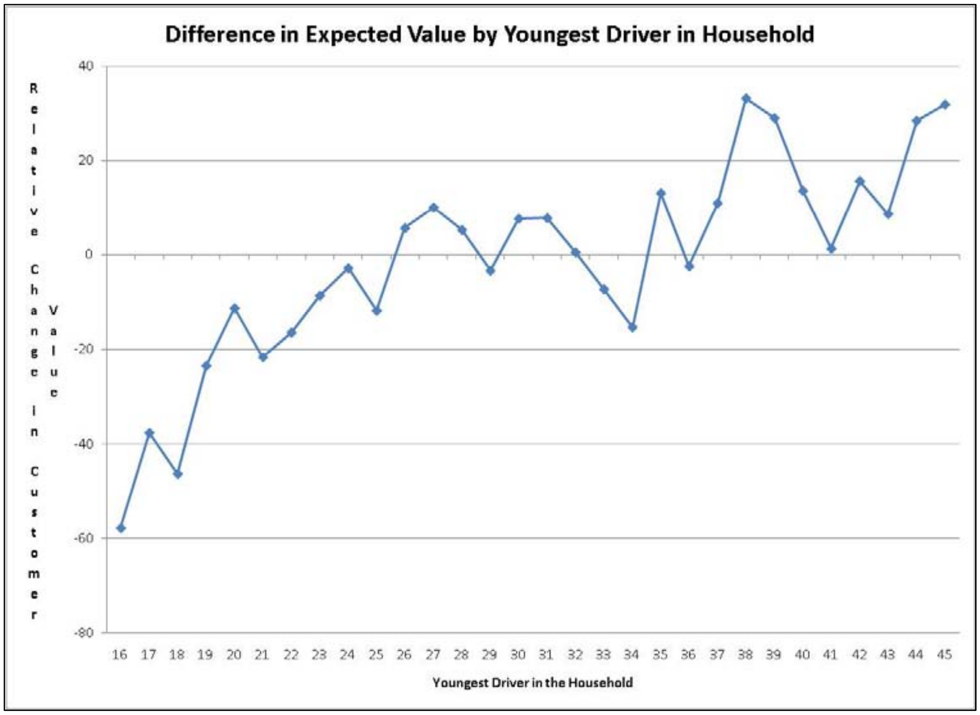

Figure 18: Change in Expected Value by Youngest Driver in Household

APPLICATIONS OF CUSTOMER VALUE MEASURES

Once a consistent measure of customer value has been developed, then a company can begin incorporating that measure of value into its business processes. There are a number of ways that this value can be recognized, and the recognition of this value will vary based on business function. However, a consistent calculation increases consistency across the organization because each department has a clear and focused vision of what constitutes a valuable customer. Examples of applications of customer value include:

1. Underwriting: The purpose of the underwriting department is to evaluate risk quality and ensure that the company is writing risks that are consistent with the company philosophy. Historically, underwriting has focused on identifying customers with better than average expected claim frequencies. As part of an underwriting process an expected customer value could be incorporated. This could adjust the underwriting workflow by allowing underwriters to focus their efforts on risks where they might have a significant impact in improving customer value, or risks on the left side of the chart in Figure 17. Underwriters would not just select insureds less likely to have a claim, but most likely to be profitable. This could also be another element in determining which new business and renewal applications are processed automatically, thus freeing the underwriter to spend more time with the more challenging risks.

2. Actuarial: The purpose of the actuarial department is to ensure that risks are being priced at a level that allows the insurer to make a reasonable profit, and that each individual risk is paying an appropriate premium. The use of a customer value by the actuarial department when determining prices will assist in balancing short term profitability with long term profitability and stability. Historically, that has been accomplished by limits on rate change or by input from the sales force. This would provide a quantitative measure to assist in this effort. The true impacts of increasing or decreasing rates can be understood in terms of the change in overall expected customer value.

3. Marketing: The marketing department can incorporate the expected customer value in the determination of the target market profile. Using expected customer value will focus not just on customers that are likely to be attracted to and purchase insurance from the company, but also whether these potential insureds are likely to be profitable customers in the future.

4. Product Managers: Product managers have the overall responsibility for the success of either all or a particular segment of a line of business. The use of expected customer value is another tool that allows the product manager to measure overall performance, and how particular courses of action might impact this expected value.

These are just a few examples of how this value can be incorporated. There are many other applications that could be developed in other areas such as claims and customer service that could help enhance customer value.

ITEMS FOR ADDITIONAL STUDY

Throughout the paper, we have discussed several practical considerations related to the calculation and application of customer value measures. There are several other considerations that need to be addressed when thinking about an approach like this.

1. Unit of Measurement

   Ultimately, customer value will be measured at the account level, which will be the customer value aggregated across multiple lines of business. However, the unit of analysis for the pieces of customer value can differ. For an expected loss analysis, the typical starting point for the analysis will be at the risk exposure level, such as coverage for auto insurance and peril or cause of loss for homeowners insurance. However, for the customer response analysis, this can be done at different levels. It can be done at the same level as the loss analysis, or it can also be performed at a more aggregate level, which may be more appropriate for modeling customer decisions. Customers may make insurance decisions at a coverage or line of business level, but often these decisions are made at the account level. An insured with multiple lines of insurance could be more likely to move their entire book of business, not just individual lines, From this perspective, analyzing customer responses at a higher level can be appropriate.

2. Insurance Regulation

   Insurance regulation is concerned with several aspects of an insurance company. From an overall perspective, regulators are concerned with the solvency of insurers, which gives the consumer more confidence that the insurer will be there to pay claims when they occur. Regulators are also concerned with the market conduct of insurance companies, ensuring that all customers are treated fairly and consistently. Another function of insurance regulation is rate regulation. Regulators are concerned that rates are not inadequate, not excessive, or not unfairly discriminatory. When insurance companies begin to understand expected customer value, any application of customer value will need to be implemented such that it does not conflict with regulation.

3. Optimization

   Once insurance companies have measured customer value, the next step is to optimize the value. The process of optimization involves maximizing customer value given the constraints that insurance companies operate under. Optimization involves targeting customer segments where the expected customer value is relatively higher, and also working with the business segments with lower than expected customer value to improve their experience. In the context of customer value, optimization involves finding the optimal premiums relative to the likelihood of attracting and retaining risks, subject to the constraints of competition, regulation, operational issues, etc.

4. Simulation

   All of the estimates of the elements of customer value have standard errors or variability associated with them, and this variability can be used to apply simulation methods to the estimation of customer value. Random variation could be introduced around the estimate of loss and customer response. The result of this analysis would be a distribution of expected outcomes, and lower and higher than average expected outcomes can be investigated to develop optimization and risk management plans.

CONCLUSION

Historically, customer value has been defined generally by insurance companies, and most quantitative definitions of value have occurred at an aggregated level and with a near term focus. In addition, definitions of customer value have varied within a company. However, with all of the additional information and the additional analysis techniques available to insurers, the elements of true customer value can be quantified. When these elements of customer value are used to develop a true customer value measure, it can lead to revelations that depart from tradition. It is these new revelations that can lead to the development of a more valuable long term book of business and more organization consistency in the definition of a valuable customer.

REFERENCES

Feldblum, S. (1990). Persistency and Profits. *Casualty Actuarial Society Discussion Paper Program , Vol 1*, 55-84.

CONTACT INFORMATION

Your comments and questions are valued and encouraged. Contact the author at:

Name: Roosevelt Mosley
Enterprise: Pinnacle Actuarial Resources, Inc.
Address: 2817 Reed Road, Suite 2
City, State ZIP: Bloomington, IL 61704
Work Phone: 309-807-2330
Fax: 309-807-2301
E-mail: rmosley@pinnacleactuaries.com
Web: www.pinnacleactuaries.com